Music Classification

July 8, 2019

In [21]:
```
import warnings
warnings.filterwarnings("ignore", category = FutureWarning)

import os
import keras
import h5py
import librosa
import itertools
import numpy as np
import matplotlib.pyplot as plt

# Preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler

from keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix

from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Activation
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Dropout
from keras.layers import Flatten
from keras.layers import BatchNormalization
```

1 Loading the Data

1.0.1 Defining general functions

In [34]:
```
# Function to split a single song into overlapping windows of the same
import more_itertools as it_plus

# def split_window(arr, genre, chunk_size=0.1, step_size=1):
```

```python
#     # Get the window size
#     window_size = int(X.shape[0]*chunk_size)
#     final_arr_x = list(it_plus.windowed(X, n=window_size, step=step_size))
#     final_arr_y = [genre for x in range(len(final_arr_x))]
#     print(final_arr_x)
#     return np.array(final_arr_x), np.array(final_arr_y)

def split_window(X, y, window = 0.1, overlap = 0.5):
    # Empty lists to hold our results
    temp_X = []
    temp_y = []

    # Get the input song array size
    xshape = X.shape[0]
    chunk = int(xshape*window)
    offset = int(chunk*(1.-overlap))

    # Split the song and create new ones on windows
    spsong = [X[i:i+chunk] for i in range(0, xshape - chunk + offset, offset)]
    for s in spsong:
        temp_X.append(s)
        temp_y.append(y)

    return np.array(temp_X), np.array(temp_y)
```

In [33]:
```python
#Function to convert songs into their respective Melspectograms
#https://github.com/Hguimaraes/gtzan.keras/blob/master/src/gtzan/struct.py

def to_melspec(song, n_fft=1024, hop_len=512):
    #Transform into spectograms
    melspec = lambda x: librosa.feature.melspectrogram(x,n_fft = n_fft,hop_length = ho
    transformed_songs = map(melspec, song)
    return np.array(list(transformed_songs))
```

In [36]:
```python
#https://github.com/Hguimaraes/gtzan.keras/blob/master/src/gtzan/struct.py

def read_data(src_dir, genres, song_samples, spec_format, chunk_size=0.1, step_size=1
    # Empty array of dicts with the processed features from all files
    arr_specs = []
    arr_genres = []

    # Read files from the folders
    for x,_ in genres.items():
        folder = src_dir + x

        for root, subdirs, files in os.walk(folder):
            for file in files:
                # Read the audio file
```

```
                file_name = folder + "/" + file
                signal, sr = librosa.load(file_name)
                signal = signal[:song_samples]

                # Debug process
                if debug:
                    print("Reading file: {}".format(file_name))

                # Convert to dataset of spectograms/melspectograms
                signals, y = split_window(signal, genres[x])

                # Convert to "spec" representation
                specs = spec_format(signals)

                # Save files
                arr_genres.extend(y)
                arr_specs.extend(specs)


    return np.array(arr_specs), np.array(arr_genres)
```

```
In [37]: print(os.getcwd()+"/genres/")
```

```
E:\Work\Case Study\Music Classification/genres/
```

```
In [38]: if not (os.path.isfile("x_gtzan_npy.npy") or os.path.isfile("y_gtzan_npy.npy")):
             # Parameters
             gtzan_dir = os.getcwd()+"/genres/"
             song_samples = 660000
             genres = {'metal': 0, 'disco': 1, 'classical': 2, 'hiphop': 3, 'jazz': 4,
                       'country': 5, 'pop': 6, 'blues': 7, 'reggae': 8, 'rock': 9}

             # Read the data
             X, y = read_data(gtzan_dir, genres, song_samples, to_melspec, debug=False)
             np.save('x_gtzan_npy.npy', X)
             np.save('y_gtzan_npy.npy', y)
```

```
In [41]: X = np.load('x_gtzan_npy.npy')
         y = np.load('y_gtzan_npy.npy')
```

1.1 Building DL models

```
In [46]: import matplotlib.pyplot as plt
         import numpy as np
         import time
         # https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
         # https://stackoverflow.com/a/14434334
         # this function is used to update the plots for each epoch and error
```

```
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

In [42]:
```
# One hot encoding of the labels
y = to_categorical(y)
```

In [44]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=
```

1.1.1 CNN

In [134]:
```
from keras.models import Sequential
from keras.layers import LSTM, BatchNormalization, TimeDistributed, Input
from keras.layers.core import Dense, Dropout
import keras
```

In [151]:
```
# Model Definition
timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
print(timesteps)
print(input_dim)
print(X_train.shape)
num_genres = 10
```

```
128
129
(13300, 128, 129, 1)
```

In [179]:
```
# inp_shape = Input(shape=X_train[0].shape)
# print(inp_shape)
# #Model 1
# model_1 = Conv2D(64,(4,4), padding='same', activation='relu')(inp_shape)
# model_1 = MaxPooling2D((2,2), strides=(1,1), padding='same')(model_1)
# model_1 = Dropout(0.5)(model_1)
# model_1 = Conv2D(128,(4,4), padding='same', activation='relu')(model_1)
# model_1 = MaxPooling2D((2,2), strides=(1,1), padding='same')(model_1)
# # model_1 = Flatten()(model_1)
# # model_1 = Dropout(0.8)(model_1)

# #Model 2
# model_2 = LSTM(64, kernel_initializer=keras.initializers.glorot_normal(seed=None),
# model_2 = Dropout(0.8)(model_2)
# model_2 = LSTM(128, kernel_initializer=keras.initializers.glorot_normal(seed=None),
# model_2 = Dropout(0.6)(model_2)
# merged = keras.layers.concatenate([model_1, model_2], axis=1)
```

```
# out = Dense(64, activation='relu')(merged)
# out = Dropout(0.7)(merged)
# out = Dense(num_genres, activation='softmax')(out)
# model = Model(input_shape, out)
# model.summary()
# model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accurac
```

In [192]:
```
# Model Definition
input_shape = X_train[0].shape
num_genres = 10

model = Sequential()
# Conv Block 1
model.add(Conv2D(16, kernel_size=(3, 3), strides=(1, 1),
                 activation='relu', input_shape=input_shape))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Dropout(0.25))

# Conv Block 2
model.add(Conv2D(32, (3, 3), strides=(1, 1), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Dropout(0.25))

# Conv Block 3
model.add(Conv2D(64, (3, 3), strides=(1, 1), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Dropout(0.25))

# Conv Block 4
model.add(Conv2D(128, (3, 3), strides=(1, 1), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Dropout(0.4))

# Conv Block 5
model.add(Conv2D(64, (3, 3), strides=(1, 1), activation='relu'))
model.add(MaxPooling2D(pool_size=(4, 4), strides=(4, 4)))
model.add(Dropout(0.3))

# MLP
model.add(Flatten())
model.add(Dense(num_genres, activation='softmax'))

model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_127 (Conv2D)          (None, 126, 127, 16)      160
```

```
_________________________________________________________________
max_pooling2d_100 (MaxPoolin (None, 63, 63, 16)        0
_________________________________________________________________
dropout_104 (Dropout)        (None, 63, 63, 16)        0
_________________________________________________________________
conv2d_128 (Conv2D)          (None, 61, 61, 32)        4640
_________________________________________________________________
max_pooling2d_101 (MaxPoolin (None, 30, 30, 32)        0
_________________________________________________________________
dropout_105 (Dropout)        (None, 30, 30, 32)        0
_________________________________________________________________
conv2d_129 (Conv2D)          (None, 28, 28, 64)        18496
_________________________________________________________________
max_pooling2d_102 (MaxPoolin (None, 14, 14, 64)        0
_________________________________________________________________
dropout_106 (Dropout)        (None, 14, 14, 64)        0
_________________________________________________________________
conv2d_130 (Conv2D)          (None, 12, 12, 128)       73856
_________________________________________________________________
max_pooling2d_103 (MaxPoolin (None, 6, 6, 128)         0
_________________________________________________________________
dropout_107 (Dropout)        (None, 6, 6, 128)         0
_________________________________________________________________
conv2d_131 (Conv2D)          (None, 4, 4, 64)          73792
_________________________________________________________________
max_pooling2d_104 (MaxPoolin (None, 1, 1, 64)          0
_________________________________________________________________
dropout_108 (Dropout)        (None, 1, 1, 64)          0
_________________________________________________________________
flatten_48 (Flatten)         (None, 64)                0
_________________________________________________________________
dense_48 (Dense)             (None, 10)                650
=================================================================
Total params: 171,594
Trainable params: 171,594
Non-trainable params: 0
_________________________________________________________________
```

In [193]:
```
X_train[0].shape
```

Out[193]: (128, 129, 1)

In [194]:
```
model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
              metrics=['accuracy'])
```

In [195]:
```
hist1 = model.fit(X_train, y_train,
          batch_size=128,
```

```
                    epochs=40,
                    verbose=1,
                    validation_data=(X_test, y_test))
```

```
Train on 13300 samples, validate on 5700 samples
Epoch 1/40
13300/13300 [==============================] - 99s 7ms/step - loss: 2.3367 - acc: 0.1909 - val_
Epoch 2/40
13300/13300 [==============================] - 98s 7ms/step - loss: 2.0150 - acc: 0.2623 - val_
Epoch 3/40
13300/13300 [==============================] - 101s 8ms/step - loss: 1.8090 - acc: 0.3523 - val
Epoch 4/40
13300/13300 [==============================] - 101s 8ms/step - loss: 1.6439 - acc: 0.4183 - val
Epoch 5/40
13300/13300 [==============================] - 101s 8ms/step - loss: 1.5231 - acc: 0.4613 - val
Epoch 6/40
13300/13300 [==============================] - 102s 8ms/step - loss: 1.4365 - acc: 0.4942 - val
Epoch 7/40
13300/13300 [==============================] - 102s 8ms/step - loss: 1.3813 - acc: 0.5115 - val
Epoch 8/40
13300/13300 [==============================] - 102s 8ms/step - loss: 1.3043 - acc: 0.5430 - val
Epoch 9/40
13300/13300 [==============================] - 102s 8ms/step - loss: 1.2677 - acc: 0.5605 - val
Epoch 10/40
13300/13300 [==============================] - 102s 8ms/step - loss: 1.2190 - acc: 0.5804 - val
Epoch 11/40
13300/13300 [==============================] - 100s 7ms/step - loss: 1.1745 - acc: 0.5956 - val
Epoch 12/40
13300/13300 [==============================] - 93s 7ms/step - loss: 1.1474 - acc: 0.6098 - val_
Epoch 13/40
13300/13300 [==============================] - 94s 7ms/step - loss: 1.1025 - acc: 0.6258 - val_
Epoch 14/40
13300/13300 [==============================] - 99s 7ms/step - loss: 1.0709 - acc: 0.6330 - val_
Epoch 15/40
13300/13300 [==============================] - 95s 7ms/step - loss: 1.0466 - acc: 0.6473 - val_
Epoch 16/40
13300/13300 [==============================] - 94s 7ms/step - loss: 1.0117 - acc: 0.6562 - val_
Epoch 17/40
13300/13300 [==============================] - 96s 7ms/step - loss: 0.9957 - acc: 0.6601 - val_
Epoch 18/40
13300/13300 [==============================] - 95s 7ms/step - loss: 0.9696 - acc: 0.6708 - val_
Epoch 19/40
13300/13300 [==============================] - 97s 7ms/step - loss: 0.9599 - acc: 0.6752 - val_
Epoch 20/40
13300/13300 [==============================] - 95s 7ms/step - loss: 0.9178 - acc: 0.6947 - val_
Epoch 21/40
13300/13300 [==============================] - 95s 7ms/step - loss: 0.9079 - acc: 0.6964 - val_
Epoch 22/40
```

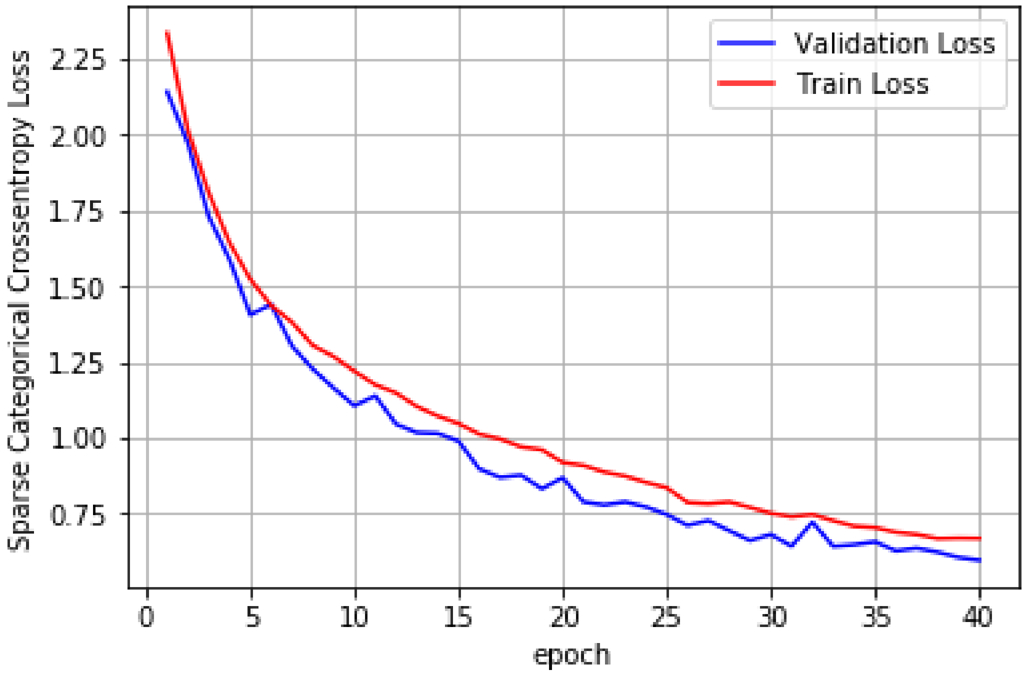
```
13300/13300 [==============================] - 95s 7ms/step - loss: 0.8863 - acc: 0.7019 - val_
Epoch 23/40
13300/13300 [==============================] - 95s 7ms/step - loss: 0.8728 - acc: 0.7053 - val_
Epoch 24/40
13300/13300 [==============================] - 96s 7ms/step - loss: 0.8519 - acc: 0.7158 - val_
Epoch 25/40
13300/13300 [==============================] - 96s 7ms/step - loss: 0.8343 - acc: 0.7222 - val_
Epoch 26/40
13300/13300 [==============================] - 97s 7ms/step - loss: 0.7856 - acc: 0.7359 - val_
Epoch 27/40
13300/13300 [==============================] - 98s 7ms/step - loss: 0.7815 - acc: 0.7388 - val_
Epoch 28/40
13300/13300 [==============================] - 97s 7ms/step - loss: 0.7875 - acc: 0.7335 - val_
Epoch 29/40
13300/13300 [==============================] - 96s 7ms/step - loss: 0.7692 - acc: 0.7441 - val_
Epoch 30/40
13300/13300 [==============================] - 99s 7ms/step - loss: 0.7500 - acc: 0.7495 - val_
Epoch 31/40
13300/13300 [==============================] - 97s 7ms/step - loss: 0.7386 - acc: 0.7533 - val_
Epoch 32/40
13300/13300 [==============================] - 98s 7ms/step - loss: 0.7459 - acc: 0.7502 - val_
Epoch 33/40
13300/13300 [==============================] - 98s 7ms/step - loss: 0.7254 - acc: 0.7595 - val_
Epoch 34/40
13300/13300 [==============================] - 100s 8ms/step - loss: 0.7072 - acc: 0.7618 - va
Epoch 35/40
13300/13300 [==============================] - 101s 8ms/step - loss: 0.7026 - acc: 0.7668 - va
Epoch 36/40
13300/13300 [==============================] - 100s 8ms/step - loss: 0.6870 - acc: 0.7678 - va
Epoch 37/40
13300/13300 [==============================] - 101s 8ms/step - loss: 0.6798 - acc: 0.7747 - va
Epoch 38/40
13300/13300 [==============================] - 100s 8ms/step - loss: 0.6663 - acc: 0.7796 - va
Epoch 39/40
13300/13300 [==============================] - 97s 7ms/step - loss: 0.6677 - acc: 0.7795 - val_
Epoch 40/40
13300/13300 [==============================] - 97s 7ms/step - loss: 0.6670 - acc: 0.7759 - val_
```

In [197]:
```python
score = model.evaluate(X_test, y_test, verbose=0)
print('Test score:', score[0])

print('Test accuracy:', score[1])
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Sparse Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,40+1))
```

```
vy = hist1.history['val_loss']
ty = hist1.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.5945673463846508
Test accuracy: 0.8049122807017544
```



1.1.2 Iterating for another 10 epochs

```
In [198]: hist2 = model.fit(X_train, y_train,
                    batch_size=128,
                    epochs=10,
                    verbose=1,
                    validation_data=(X_test, y_test))
```

```
Train on 13300 samples, validate on 5700 samples
Epoch 1/10
13300/13300 [==============================] - 96s 7ms/step - loss: 0.6364 - acc: 0.7912 - val_
Epoch 2/10
13300/13300 [==============================] - 96s 7ms/step - loss: 0.6333 - acc: 0.7910 - val_
Epoch 3/10
13300/13300 [==============================] - 99s 7ms/step - loss: 0.6286 - acc: 0.7886 - val_
Epoch 4/10
```

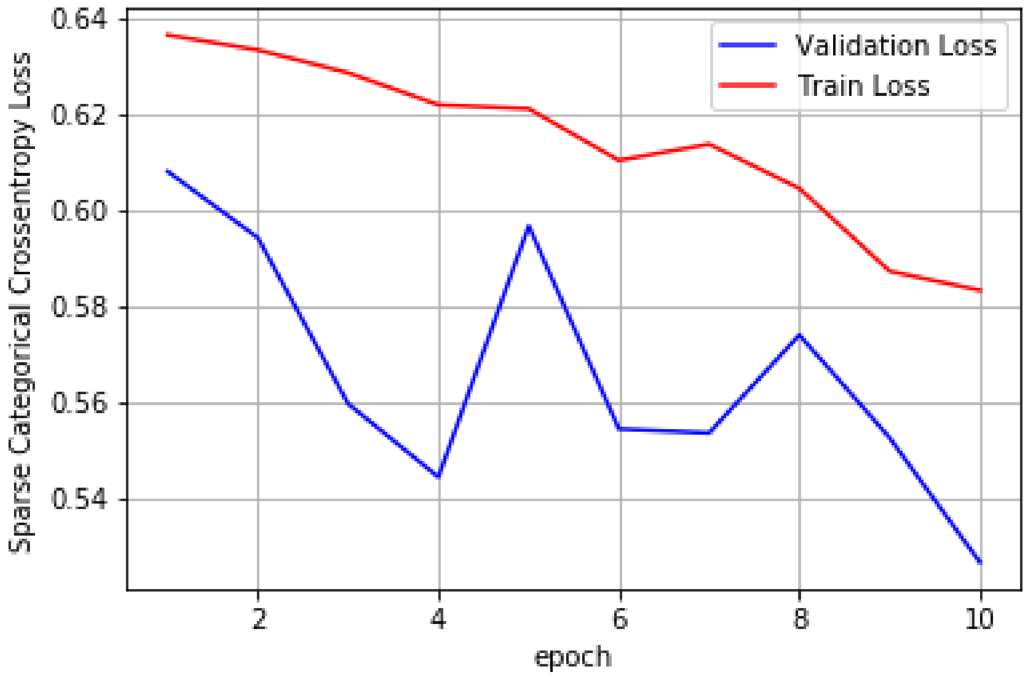
```
13300/13300 [==============================] - 97s 7ms/step - loss: 0.6219 - acc: 0.7922 - val_
Epoch 5/10
13300/13300 [==============================] - 96s 7ms/step - loss: 0.6211 - acc: 0.7890 - val_
Epoch 6/10
13300/13300 [==============================] - 98s 7ms/step - loss: 0.6103 - acc: 0.7923 - val_
Epoch 7/10
13300/13300 [==============================] - 98s 7ms/step - loss: 0.6137 - acc: 0.7938 - val_
Epoch 8/10
13300/13300 [==============================] - 98s 7ms/step - loss: 0.6045 - acc: 0.8006 - val_
Epoch 9/10
13300/13300 [==============================] - 96s 7ms/step - loss: 0.5873 - acc: 0.8030 - val_
Epoch 10/10
13300/13300 [==============================] - 98s 7ms/step - loss: 0.5833 - acc: 0.8038 - val_
```

In [199]:
```python
score = model.evaluate(X_test, y_test, verbose=0)
print('Test score:', score[0])

print('Test accuracy:', score[1])
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Sparse Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,10+1))


vy = hist2.history['val_loss']
ty = hist2.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
Test score: 0.5268087197186654
Test accuracy: 0.8278947368421052
```




```
In [200]: model.save("music_genre_classn.h5")

In [ ]:
```